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ECBC-TR-353

LINGUISTIC-FUZZY CLASSIFIER FOR DISCRIMINATION AND CONFIDENCE VALUE ESTIMATION

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14. ABSTRACT
This report describes a new method for assigning an event to a particular class. An event is described by some attributes (e.g., size, shape, and intensity and their changes). These attributes have a distribution. Fuzzy membership functions provide a means for quantifying the importance of an attribute based on its value and distribution. With proper selection of attributes, we can calculate the probability that an event belongs to a particular class by selecting appropriate membership functions. We applied this to visible and IR camera data generated to support the DSI Program. The goal of the program is to investigate the possibility of using disparate sensors to serve as a chemical and biological early warning system and integrate them into the CB command and control network. Detecting when CB munitions are deployed requires developing algorithms that differentiate between the detonation of conventional and CB munitions. This report describes how we applied this new classification method to video signals generated from the visible cameras used during DSI field test. The report provides examples of how to use this method to estimate class confidence and will also show how the confidence values were used to discriminate between CB and conventional munitions' detonations.

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PREFACE

The work described in this report was authorized under Project No. 206023.84BPO. This work was started in December 2002 and completed in August 2003.

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1. INTRODUCTION

In September 2001, the U.S. Army Edgewood Chemical Biological Center (ECBC) conducted a field test at Dugway Proving Ground [(DPG), Dugway, UT)]. The test was part of the Disparate Sensor Integration (DSI) program and was intended to collect signatures of conventional high explosive (HE) and simulated chemical/biological (CB) artillery rounds. During the test, 260 155mm artillery rounds were fired. One hundred sixty of these munitions were of known class and their signatures were used to help identify critical features and develop algorithms to distinguish between the different munition classes. The last 100 rounds were blind (to the analyst) and were used to test the robustness of the discriminating algorithms. The rounds were divided equally between HE and simulated CB rounds. The conventional rounds contained 15 lb of HE, while the CB rounds contained about 1.5 lb of HE and were filled with a 50-50% mixture of water and poly ethylene glycol. Half of the munitions were fused to detonate on ground impact. The other half were fused for airburst. The rounds were fired in random order. A detailed description of the test is given in ECBC-TR-251.[1]

In support of the DSI Program, several camera systems were fielded to determine the feasibility of using information from these systems to discriminate between chemical and conventional munitions. The systems fielded included two visible wavelength range cameras, a near infrared (IR) camera (peak responsivity at approximately 1 μm), a mid-range IR camera (3 μm - 5 μm), and a long wavelength IR camera system (7.5 μm - 13 μm).

One of the imaging systems was DPG's Sony DSR-2000, which is sensitive over the visible spectrum. The video data were transformed to .avi files using an INDEO5 CODEC. The frame rate for these video sequences was approximately 30 feet per second (fps) frames. The images from these .avi files have a 640 x 480 pixel resolution. The Sony camera is a 3-CCD camera. However, the methods used to archive the video data and to transform the data to .avi files removed many of the benefits normally obtained when using a 3-CCD camera. Consequently, the video data is equivalent in image quality to that which can be captured from many different visible camera systems, including those currently fielded on the battlefield for surveillance.

References 2, 3, and 4 provide descriptions of methods used to identify frames of interest in the .avi video files. Reference 4 describes the methods used on long wavelength range IR imaging systems, but the method used is essentially the same. References 2 and 3 describe features that can be extracted from specific video sequence frames and how these features can be used for discrimination using linear thresholding in a variety of two-dimensional scatter plots.

In this report, we first describe features extracted from each video frame of interest. We show how these features are collapsed to a single feature vector used as an input to a classifier to discriminate between an HE and a CB event. Following this, we describe the

linguistic-fuzzy classifier and show how it is used to generate confidence values for each potential target class. This is followed by a discussion of how the confidence values are used to discriminate between classes. We conclude with a discussion of the results obtained using these methodologies on the DSI visible camera data set.

2. DESCRIPTIONS OF FEATURE SETS

Reference 4 provides a detailed description of the methods used to identify "frames" of interest in video sequences. In summary, the method includes subtracting from the image being examined in the background (20 frames prior to the frame being examined) to create a "change" image and binarizing the change image using adaptive thresholding methods to emphasize the area in the image associated with the detonation signature. References 2 and 3 describe a number of features that are potentially useful for discriminating between the four different classes of munitions' detonations. This report provides detailed descriptions of the features and the methods used to extract them from up to four video frames providing the information used for discrimination.

Table 1 provides an example of the features extracted from a typical video sequence (in this case for a CB airburst detonation). The "detector" described in detail in Reference 4 was used to evaluate the DSI video files. (Note that this detector is slightly modified to afford an ability to detect light and dark (versus dark only) munitions' detonation signatures.) Each time the detector triggers, the frame number as well as extracted features are written to a file. When the first frame is detected, the detonation video sequence starts. We examine 10 frames in the detonation sequence. We extract features from the first frame on which the detector triggers, plus up to three additional frames. We try to extract features from the 2nd and 3rd frames in the detonation video sequence. If the detector does not trigger on these frames, we extract features from the first two frames on which the detector triggers (or from less frames if the detector does not trigger two additional times during the first 10 frames of a detonation sequence). We always attempt to extract features from the 10th frame in the video sequence. When working with this last frame, features are extracted only if the detector triggers on this video frame. In general, for strong munitions' detonation signals, the detector will trigger, and features will be extracted from the 1st, 2nd, 3rd, and 10th frames after munitions' detonations. When the signatures are less strong, the detector may only trigger on (and features will be extracted from) the first three frames after detonation, or the 1st, 3rd, 5th, and 10th frames or just on the 1st and 2nd frames. (Note that there are many possibilities for the detector to trigger during a particular video sequence, and that the specifics of its triggering are generally driven by the specific characteristics of the munition's detonation signature.) In the DPG visible camera video files, the detector triggered at least once on all but 1 of the 260 video files.

For each frame on which the detector triggers, the following information is extracted and written to file - the video sequence file name, the frame number, and four feature values. An example of such a file is provided in Table 1. The four features are a grayscale feature, which is proportional to the contrast between the detected signal and the background, the orientation angle (with respect to the horizontal) of a binarized version of the detected signal,

the number of blobs in the image after binarization, and the total number of "on" pixels in the image after binarization. Note that these features and the methods for extracting them have been described in detail in References 2 and 3.

Table 1. Features Extracted From Four Video Frames

Filename	Frame Number	Orientation	Delta Gray Feature	Number of Blobs	Average Number of Pixels/Blob
T173DVV00CXX	117	-71.57	-1.5	1	4
T173DVV00CXX	118	-33.69	18.55	1	38
T173DVV00CXX	119	-52.48	19.68	1	50
T173DVV00CXX	126	-55.38	-5.78	1	65
4					

Next we consolidate the information from these four (or less) frames to create a single feature vector. We summarize this process in the discussion below. The number 4 at the bottom of Table 1 indicates that the detector triggered on four frames. As discussed above, in some video sequences, the detector triggers on less than four frames. This occurs most often for the chemical simulant point detonations (and occasionally with the HE point detonations) and is generally a result of the low contrast between point detonation signatures and the background. In all cases, the features provided in Table 1 are combined to create a single feature vector for the particular file being analyzed. It is this final feature vector that is used as input to discrimination algorithms used for classification. Below, we describe how the features are combined. (Note that the feature names highlighted in bold below are the features that make up the final feature vector and not those previously provided in Table 1.):

a. Set the **orientation feature** to the value associated with the 10th frame after detonation (4th row of Table 1). If the detector triggers less than four times, the orientation feature is set to zero.

b. Set the **delta gray feature** to the average of the delta gray feature values from the 2nd and 3rd frames (2nd and 3rd row of Table 1). If the detector triggers twice, set this feature's value to ½ the delta gray feature value associated with the 2nd frame. If the detector triggers only once, set this feature's value to zero. The absolute and signed values of the delta gray feature are used in the final feature vector. Positive delta gray feature values are associated with munitions' detonation signatures that are darker than the median background intensity level, and negative delta gray feature values are associated with munitions' detonation signatures that are lighter than the median background intensity level. The absolute value of this feature is proportional to the contrast between the munition's detonation signature and the median background intensity level.

c. Set the **size1 feature** value to the number of "on" (non-zero) pixels in the last frame in which the detector triggered (e.g., the 10th frame if the detector triggered four times or the 3rd frame if the detector triggered three times).

d. Set the **size2 feature** value to the cumulative sum of "on" (non-zero) pixels for all frames in which the detector triggered.

e. Set the **sequential feature** to 1 if the detector triggers on the first three and 10^{th} frames in the detonation video sequence. Set the **sequential feature** to 0 if the detector does not trigger on the first three and 10^{th} frames after a munition's detonation.

f. Set the **blobs4 feature** to the number of objects in the biniarized image in the 10^{th} frame after detonation. Set the **blobs4 feature** to 0 if the detector does not trigger on the 10^{th} frame.

Using the methods described above, the features in Table 1 are reduced to a single feature vector (Table 2) that will be used for classification.

Table 2. Feature Vector Generated From Features Provided in Table 1

File Name	Orientation	Absolute Delta Gray	Delta Gray	Size1	Size2	Blobs4	Sequential
T173DVV00CXX	- 55.38	19.115	19.115	65	157	1	1

The feature vectors shown in Table 2 were generated for each of the training and blind munitions' detonation events associated with the DSI program. The linguistic-fuzzy classifier uses these feature vectors as input and output confidence values. As described later in this report, these confidence values can be used as a basis for discrimination. They can also be potentially useful inputs for multisensor data fusion engines that would fuse the outputs of this sensor with those from other DSI sensors.

3. LINGUISTIC-FUZZY CLASSIFIER APPLIED TO DSI FEATURE VECTORS

References 2 and 3 provide a detailed description of the initial methodologies used to classify the training and blind events in the Dugway visible camera DSI data set. Classification was initially accomplished through development of scatter plots in two-dimensional feature spaces. Automated classification was accomplished by applying linear thresholds to separate the classes in the two-dimensional spaces. In this section, we will first briefly describe the method originally used to classify events as either airburst or point detonations. This will be followed by a description of the linguistic-fuzzy classifier used to develop two confidence values (one for airburst and one for point detonation) for detonation events. Next, the other linguistic-fuzzy classifiers used to separate the four classes of detonation events associated with the DSI Program will be discussed in detail. Section 4 of this report provides specific examples of the confidence values generated on the DSI training set using the methods described in this section. This section will also include a discussion of how these confidence values are used to classify events.

To discriminate between chemical munition and HE detonations, we found it advantageous to first separate the data into airburst and point detonation classes. Once this initial classification was accomplished, it was significantly easier to separate the chemical and HE munition classes.

Figure 1 provides a scatter plot in the two-dimensional feature space used for separating the airburst and point detonation classes. The features used for this purpose were the absolute value of the delta gray feature (Y axis) and the orientation feature (X axis). The data presented in Figure 1 were generated using the DSI visible camera training data set.

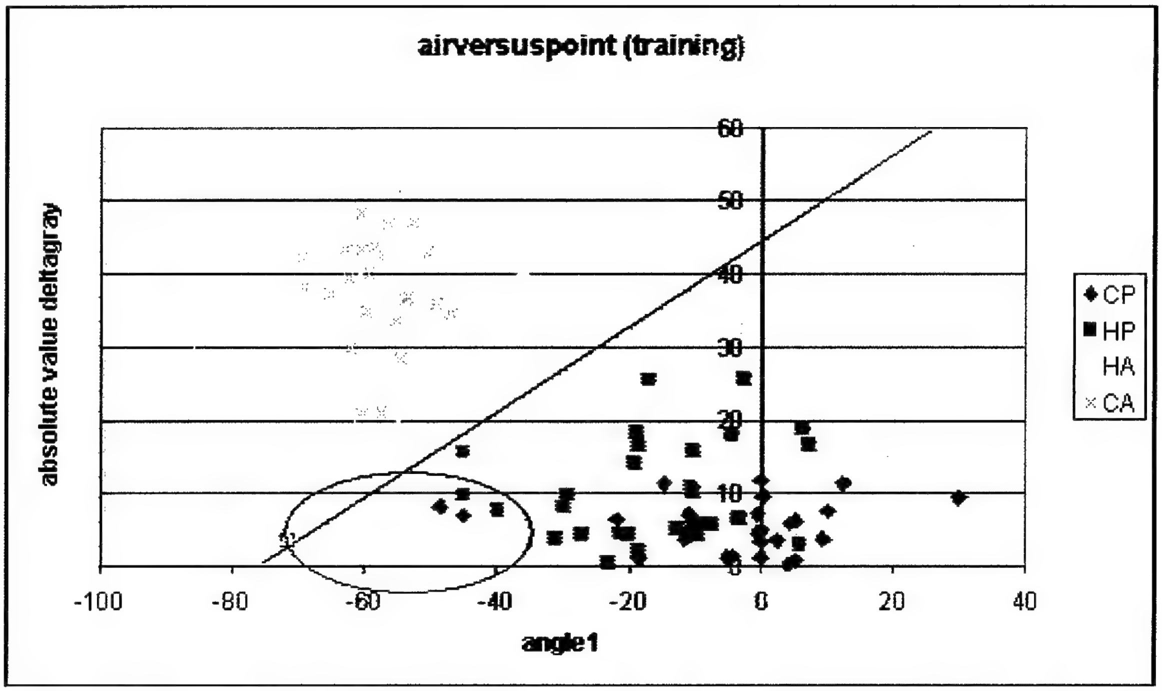

Figure 1. Scatter Plot - Absolute Value Delta Gray Versus Orientation. The line shown in the figure is used to separate the two munitions' detonation classes.

The data in Figure 1 clearly show the clustering of the different detonation classes in this two-dimensional feature space in the training data set. There are two clear clusters: (1) one at relatively small levels of the absolute value of delta gray and relatively small orientation angles, and (2) one at larger levels of the absolute value of delta gray and smaller (more negative) values of the orientation angle. In both cases, many of the points outside these clusters are a direct result of how the current routines deal with the cases where there are multiple blobs within the binary image associated with the frame being analyzed. The line in the plot is used to separate the two cluster groups (above the line are air detonations and below the line are point detonations). This two-dimensional feature space and the indicated line were used to classify the DSI blind events as either airburst or point detonation. In the scatter plots, points that are sufficiently close to the line such as those circled were classified as indeterminate, and were further evaluated as air and point detonations.

With the linguistic-fuzzy classifier, targets are first described in terms of their attributes. For the case shown in Figure 1, the following descriptions are used:

- **Air detonations** have a **preferred orientation** and **higher values of the absolute value of delta gray**

- **Point detonations** have an **orientation near zero** and **lower values of the absolute value of delta gray**

The words in bold in the above descriptions are the class for which we want to generate a confidence value and a verbal description of the class' feature properties.

Figure 2 provides histograms generated from the DSI training data set. In all of the histogram plots provided in this section, the X-axes are the feature values. The Y-axes are the number of cases of this feature value in a particular feature distribution. For aesthetic reasons, the Y-axis is clipped at a value of 3. The histograms of the orientation feature for the two classes of detonation modes are shown on the plot on the left in Figure 2. The red histogram is for the point detonations, while the blue histogram is for the airburst detonations. The plot on the right shows histograms of the absolute value of the delta gray feature. Again, the red histogram is for point detonations, and the blue histogram is for airburst detonations. Note that these are the same data shown in the scatter plot in Figure 1.

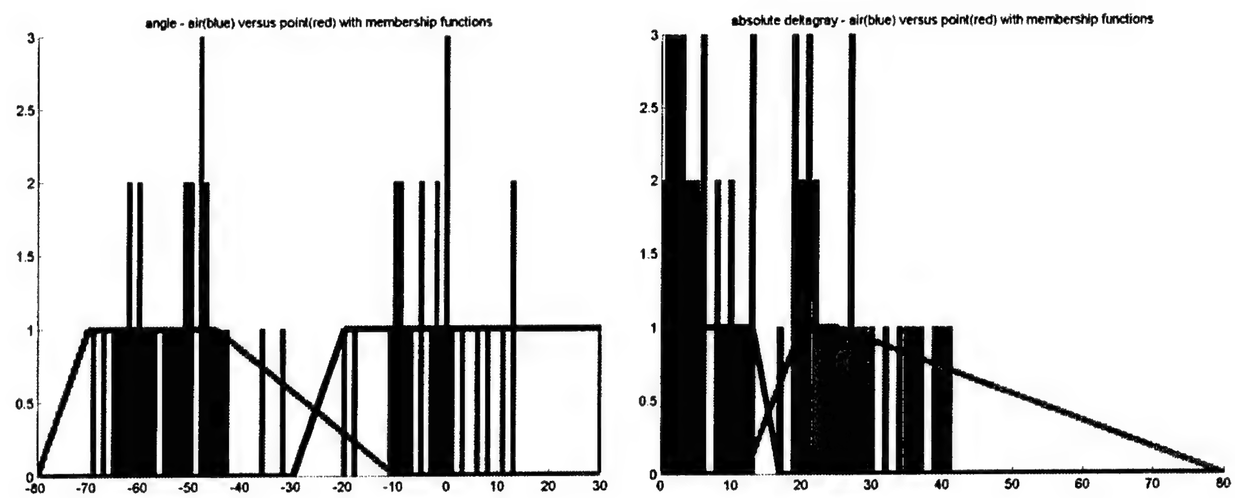

Figure 2. Histograms and Membership Functions for Air Detonation Versus Point Detonation Classification.

Membership functions for these data features are also shown in Figure 2. The green membership functions were generated based on the blue histogram distributions, and the black curves were generated from the red histograms. The membership functions are empirically derived based on manual analyses of the histograms shown in this figure. Automating the generation of these histograms is ongoing and will be discussed in a future report.

A description of how these membership functions are used follows. To discuss this, the plot on the left of Figure 2 will be used. The green membership function is used to define **preferred orientation** that was used in the target class descriptions provided earlier in this section. The black membership function is used to define **orientation near zero** that was used in the target class descriptions provided earlier. The membership of a particular feature value is determined by its intersection with the membership function shown in the plot. For example, if the orientation feature has a value of - 60°, it results in a 100% membership in **preferred orientation** and a 0% membership in **orientation near zero**. For another example, if the orientation feature has a value of 0°, it results in a 0% membership in **preferred orientation** and a 100% membership in **orientation near zero**. As a final example, if the orientation feature has a value of - 25°, it results in a membership of 50% in **preferred orientation** and a membership of 50% in **orientation** (note that it is not necessary that membership values for both attributes add up to 100%). It is the overlap of these membership functions that makes this a fuzzy method.

In the case shown in Figure 2, feature values contribute equally to being able to properly classify events as either air or point detonations (e.g., there are about the same number of red lines under the green curves in both plots and blue curves under the black line in both plots). Consequently, it was decided to weight these two features equally when developing confidence values for the detonation mode of events as either point or air detonations.

To generate a confidence value for air detonations, we define a confidence function defined by the following expression:

$$\mathrm{Conf}_{\mathbf{airburst}} = (W_{\textit{preferred orientation}} * \mathrm{Mem}(\textbf{\textit{preferred orientation}}))^2 + (W_{\textit{higher values of the absolute value of delta gray}} * \mathrm{Mem}(\textbf{\textit{higher values of the absolute value of delta gray}}))^2 / (W_{\textit{preferred orientation}}^{\ 2} + W_{\textit{higher values of the absolute value of delta gray}}^{\ 2}) \qquad (1)$$

where

$\mathbf{Conf}_{\mathrm{airburst}}$	= confidence that the observed detonation is an airburst detonation – maximum value is 1 (100% confidence), and minimum value is 0 (0% confidence)
$W_{\textit{preferred orientation}}$	= weight for the orientation feature = 1
$W_{\textit{higher values of the absolute value of delta gray}}$	= weight for the absolute value delta gray feature = 1
Mem(***preferred orientation***)	= membership of the orientation feature value in the **preferred orientation** membership function shown (green) in Figure 2.
Mem(***higher values of the absolute value of delta gray***)	= membership of the absolute value of the delta gray feature value in **higher values of the absolute value of delta gray** membership function shown (green) in Figure 2.

The specific membership functions and weights used in the above relationship are based on analyses of the histograms of the feature distributions within a given class. The key to the meaningfulness of this confidence value is the proper selection of membership functions and weights.

To generate a confidence value for point detonations, the following expression is used:

$$\mathrm{Conf}_{\mathbf{point}} = (W_{\textit{orientation near zero}} * \mathrm{Mem}(\textbf{\textit{orientation near zero}}))^2 + (W_{\textit{lower values of the absolute value of delta gray}} * \mathrm{Mem}(\textbf{\textit{lower values of the absolute value of delta gray}}))^2 / (W_{\textit{orientation near zero}}^{\;2} + W_{\textit{lower values of the absolute value of delta gray}}^{\;2}) \quad (2)$$

where

$\mathrm{Conf}_{\mathbf{point}}$	= confidence that the observed detonation is a point detonation – maximum value is 1 (100% confidence), and minimum value is 0 (0% confidence)
$W_{\textit{orientation near zero}}$	= weight for the orientation feature = 1
$W_{\textit{lower values of the absolute value of delta gray}}$	= weight for the absolute value delta gray feature = 1
Mem(***orientation near zero***)	= membership of the orientation feature value in **orientation near zero** membership function shown (black) in Figure 2.
Mem(***lower values of the absolute value of delta gray***)	= membership of the absolute value of the delta gray feature value in **lower values of the absolute value of delta gray** membership function shown (black) in Figure 2.

Again, specific membership functions and weights used in the above relationship are based on analyses of the histograms of the feature distributions within a given class. Section 4 provides examples of the use of the above relationships for generating confidence values for air and point detonations.

When an event is classified as an air detonation, a new set of relationships are used to generate confidence values for whether the munition's detonation is from either a CB or an HE round. Figure 3 provides the histograms and membership functions used for generating these confidence values.

The green histogram distributions are generated from HE air detonation events in the DSI visible camera data set. The red distributions are generated from the CB air detonation events in the DSI visible camera data set. The blue membership functions are those used for generating HE confidence values, and the black distributions are used for generating CB confidence values.

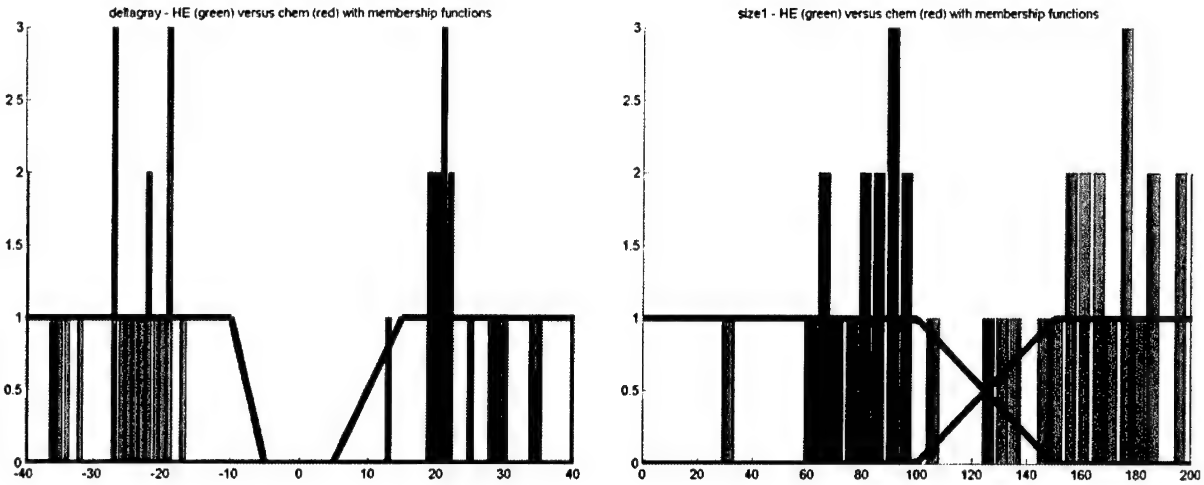

Figure 3. Histograms and Membership Functions for CB Versus HE Classification for Air Detonations.

The following descriptions are used for these two target classes:

- **HE detonations** have a **large size1** and **negative delta gray** feature values
- **CB detonations** have **smaller size1** and **positive delta gray** feature values

A quick analysis of the plot on the left (delta gray) shows that the two classes are almost completely separable using this feature and the membership values shown. In the plot on the right (size1), there are more discrepancies in classification using the shown membership functions. Consequently, the weight for the delta gray feature should be higher than that for the size1 feature. This will be reflected in the relationships used to generate confidence values for these two classes.

The above descriptions are then used to generate confidence values. To generate a confidence value for HE air detonations, the following relationship is used:

$$\mathrm{Conf}_{\mathbf{HEair}} = (W_{large\ size1} * \mathrm{Mem}(\boldsymbol{large\ size1}))^2 + (W_{negative\ delta\ gray} * \mathrm{Mem}(\boldsymbol{negative\ delta\ gray}))^2 / (W_{large\ size1}^{\ 2} + W_{negative\ delta\ gray}^{\ 2}) \tag{3}$$

where

$\mathrm{Conf}_{\mathbf{HEair}}$	= confidence that the observed detonation is an HE airburst detonation - maximum value is 1 (100% confidence), and minimum value is 0 (0% confidence)
$W_{large\ size1}$	= weight for the size1 feature = 0.75
$W_{negative\ delta\ gray}$	= weight for the delta gray feature = 1

Mem(***large size1***) = membership of the size1 feature value in **large size1** membership function shown (blue) in Figure 3.

Mem(***negative delta gray***) = membership of the delta gray feature value in **negative delta gray** membership function shown (blue) in Figure 3.

To generate a confidence value for CB air detonations the following relationship is used:

$$\mathrm{Conf}_{\mathbf{HEair}} = (W_{smaller\ size1}{*}\mathrm{Mem}(\boldsymbol{smaller\ size1}))^2 + (W_{positive\ delta\ gray}{*}\mathrm{Mem}(\boldsymbol{positive\ delta\ gray}))^2 / (W_{smaller\ size1}^{\ 2} + W_{positive\ delta\ gray}^{\ 2}) \quad (4)$$

where

$\mathrm{Conf}_{\mathbf{HEair}}$ = confidence that the observed detonation is a CB airburst detonation - maximum value is 1 (100% confidence), and minimum value is 0 (0% confidence)

$W_{smaller\ size1}$ = weight for the size1 feature = 0.75

$W_{positive\ delta\ gray}$ = weight for the delta gray feature = 1

Mem(***smaller size1***) = membership of the size1 feature value in **smaller** size1 membership function shown (black) in Figure 3.

Mem(***positive delta gray***) = membership of the delta gray feature value in **positive delta gray** membership function shown (black) in Figure 3.

The real advantage of the linguistic-fuzzy classifier is that it can be implemented to consider the different features' dependence on distance. As mentioned in References 2 and 3, a significant change in focal length occurred between the training and blind detonation events. (Note that changing focal length is nearly equivalent to changing the source to camera distances.) The relationships provided above were used on the training and blind data sets. To compensate for the change in focal length, the membership functions were modified. In this case, they were modified by multiplying them by the ratio of the median of the size1 feature value from the blind data set and the median value of the size1 feature value from the training data set. Since we can calculate (through analyses) how this multiplication factor should vary with different camera-to-source distances, membership functions can be adjusted to accommodate such a change. In addition, because the DSI seismic and acoustic sensors can determine the location of detonations and consequently the camera-to-source distances, this information will allow for the "dynamic" determination of the value of the discriminating feature, and hence modification of membership functions. This is one of the significant advantages to the particular sensor suite fielded in support of the DSI Program. (Note also that an accurate time of detonation, which is available from the camera systems, significantly improves the acoustic and seismic sensor arrays' abilities to determine detonation locations).

Examples of confidence values generated using the methods described above, and their success in classifying the DSI training data set are provided in Section 4.

When an event is classified as a point detonation, another set of target class descriptions are used to discriminate between the CB and the HE munitions. Figure 4 provides the histograms and membership functions for three of the four features used to differentiate between these two types of detonation events.

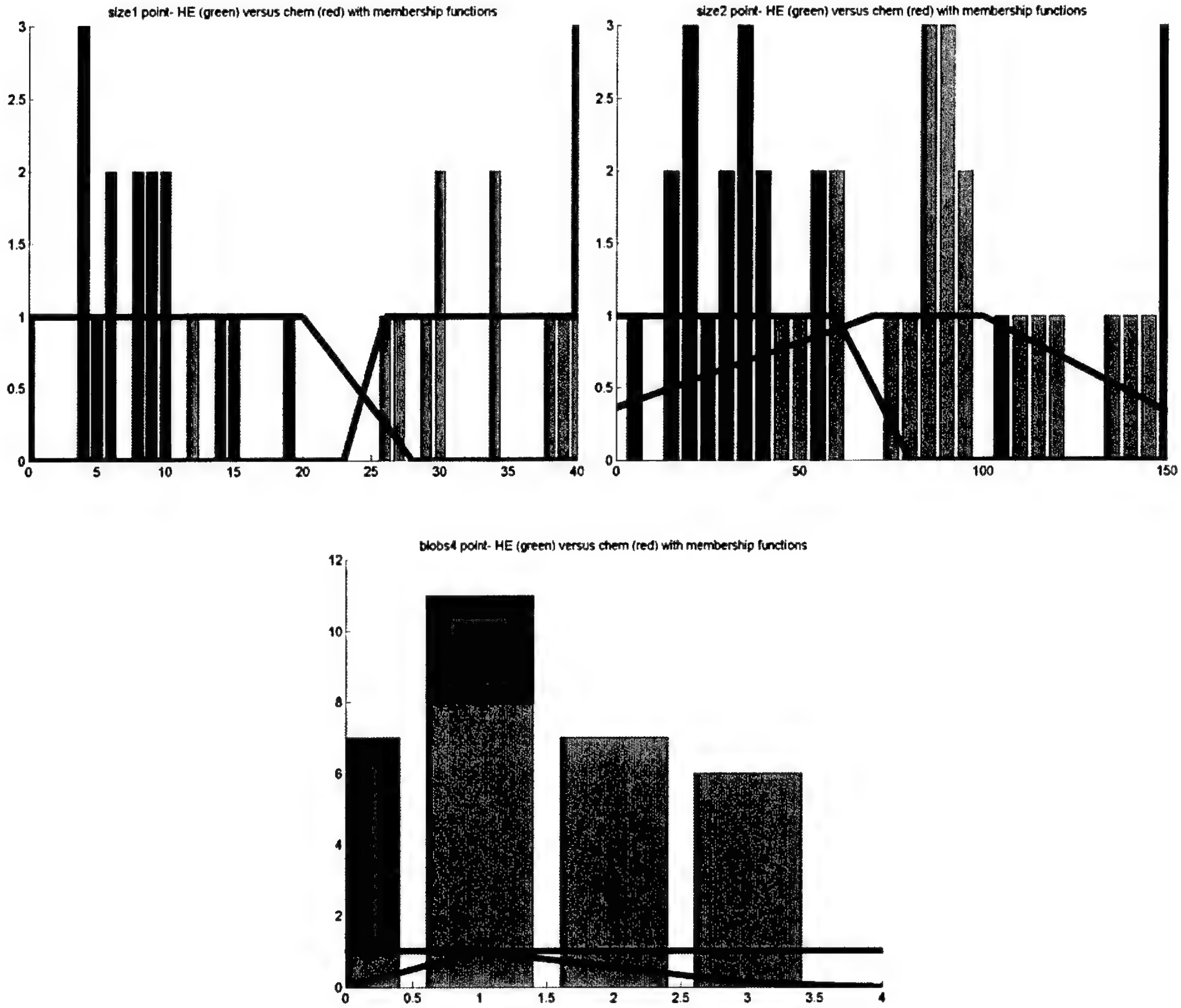

Figure 4. Histograms and Membership Functions for CB Versus HE Classification for Point Detonations.

The green histogram distributions are generated from HE point detonation images in the visible range. The red distributions are generated from the CB point detonation images. The blue membership functions are those used to generate HE confidence values, and the black distributions are used to generate CB confidence values. The four features used for confidence generation with point detonation events are size1, size2, blobs4, and the sequential features' values. The plot in the upper left is the size1 feature distribution. The plot in the upper right is the size2 feature value. Also, the size2 values generated from CB air detonations are shown in

purple on this plot. The close proximity to the higher values associated with the HE distribution for point detonations is the main reason the membership function for HE events for this feature value is reduced with higher values of the size2 values. Histograms for the fourth feature are not provided as this is a binary feature (the detector either triggered four times in the "usual" sequence or did not - to gain insight into the importance of this feature in performing classification, please refer to the data provided in Table 3).

The following descriptions are used for these two detonation event classes:

- **HE point detonations** have a **large size1**, **large size2**, **higher values of blobs4,** and are **sequential.**

- **CB point detonations** have a **small size1**, **small size2**, **lower values of blobs4,** and are **not always sequential.**

Analyses of the histograms and membership functions provided in Figure 4, show that the size1 feature provides the best separation between these two classes of munitions' detonation events. In the histograms and membership functions shown in the upper left in Figure 4, there is effectively only one HE munition's detonation event under the black membership function that describes **small size1** feature values. The extension of this membership function to higher size1 feature values than those indicated in the histogram for CB munitions' detonations affords the classifier increased robustness when dealing with the variability of "real world" data. If for example, in a blind event, the value of size1 increases slightly above the values indicated in the histogram, the extension of the membership function affords an ability for the classifier to appropriately use this feature value since it evolves a confidence estimation. This tends to afford the classifier an ability to work over a range of distance (or zoom factor) values without requirements to range normalize features or modify membership functions. However, it will still be required either to modify membership functions (or normalize the feature values) with more significant changes in either range (or zoom factor).

There is also reasonable separation between the two classes of munitions' detonations when considering the size2 feature. In the histograms and membership functions shown in the upper right in Figure 4, there are four instances of HE events that fall under the membership function for **small size2** feature values. There are significantly greater numbers of CB events that fall under the membership function for **large size2** feature values. The shape of the membership function associated with **small size2** feature values is intuitive based on the histogram distributions shown in Figure 4. Extending this membership function to higher size2 feature values again is done to increase the robustness of the system when dealing with "real world" data. The shape of the **large size2** membership function is less intuitive. We taper this membership function off at higher values of the size2 feature values because there are slight overlaps in the size2 feature histogram distributions for HE point detonations and CB airburst distributions. This is important when dealing with cases where the confidence values associated with point and airburst detonations are similar. Tapering the **large size2** membership function at lower size2 feature values was selected as shown because it is important in achieving proper classification for the two HE detonation events in which the size2 feature value was around 50.

This tapering also affords increased robustness when dealing with "real world" data. Because the separation in classes was not as good with the size2 feature as it was with the size1 feature, this feature will be weighted less than the size1 feature when estimating class confidences.

The blobs4 feature also shows some ability to separate the two classes of munition detonation events. In this case (bottom plot, Figure 4), there is only one example where the blobs4 feature value is 0 for an HE munition's detonation. When the blobs4 feature value is 1, there are approximately an equal number of cases where the detonations are either HE or CB. There are no instances where a CB event produces a blobs4 feature value >1. Note that the blobs4 feature is constrained to be an integer (0 or positive). The black membership function shown in Figure 4 is for **lower values of blobs4**, and the blue membership function is for **higher values**. We chose once again to extend the limits of the membership function beyond the values indicated in the histograms. This is done to increase the overall robustness of the classifier because it affords a better means for this feature's value to drive the confidence value appropriately for HE and CB munitions' detonations. Since there is significantly more overlap of the classes with this feature value, it will be weighted less than either the size1 or size2 feature values in the linguistic-fuzzy system used to estimate confidence values.

The previously provided target class descriptions are next used to generate confidence functions. To generate a confidence value for HE point detonations, the following relationship is used:

$$\mathrm{Conf}_{\mathbf{HEpt}} = (W_{large\ Size1}*\mathrm{Mem}(\boldsymbol{large\ size1}))^2 + (W_{large\ Size2}*\mathrm{Mem}(\boldsymbol{large\ size2}))^2 + (W_{higher\ values\ of\ blobs4}*\mathrm{Mem}(\boldsymbol{higher\ values\ of\ blobs4}))^2 + (W_{sequential}*\mathrm{Mem}(\boldsymbol{sequential}))^2 / (W_{large\ size1}^2 + W_{large\ size2} + W_{higher\ values\ of\ blobs4}^2 + W_{sequential}^2) \quad (5)$$

where

$\mathrm{Conf}_{\mathbf{HEpt}}$	= confidence that the observed detonation is an HE point detonation - maximum value is 1 (100% confidence), and minimum value is 0 (0% confidence)
$W_{large\ size1}$	= weight for the size1 feature = 1
$W_{large\ size2}$	= weight for the size2 feature = 0.8
$W_{higher\ values\ of\ blobs4}$	= weight for the blobs4 feature = 0.7
$W_{sequential}$	= weight for the sequential feature = 0.5
Mem(***large size1***)	= membership of the size1 feature value in **large size1** membership function shown (blue) in Figure 4.
Mem(***large size2***)	= membership of the size2 feature value in **large size2** membership function shown (blue) in Figure 4.

Mem(***higher values of blobs4***) = membership of the blobs4 feature value in **higher values of blobs4** membership function shown (blue) in Figure 4.

Mem(***sequential***) = 1 if the detector triggering is "sequential," and 0 if the detector triggering is not "sequential."

To generate a confidence value for CB air detonations, the following relationship is used:

$$\begin{aligned} Conf_{\mathbf{CBpt}} = {} & (W_{small\,size1}{*}Mem(\textbf{\textit{small size1}})^2 + (W_{small\,size2}{*}Mem(\textbf{\textit{small size2}})^2 \\ & + (W_{lower\,values\,of\,blobs4}{*}Mem(\textbf{\textit{lower values of blobs4}})^2 \\ & + (W_{not\,always\,sequential}{*}Mem(\textbf{\textit{not always sequential}})^2/(W_{small\,size1}{}^2 \\ & + W_{small\,size2}{}^2 + W_{lower\,values\,of\,blobs4}{}^2 + W_{not\,always\,sequential}{}^2) \end{aligned} \quad (6)$$

where

$Conf_{\mathbf{CBpt}}$ = confidence that the observed detonation is a CB point detonation - maximum value is 1 (100% confidence), and minimum value is 0 (0% confidence)

$W_{small\,size1}$ = weight for the size1 feature = 1

$W_{small\,size2}$ = weight for the size2 feature = 0.8

$W_{lower\,values\,of\,blobs4}$ = weight for the blobs4 feature = 0.7

$W_{not\,always\,sequential}$ = weight for the feature that is not always sequential = 0.5

Mem(***small size1***) = membership of the size1 feature value in **small size1** membership function shown (black) in Figure 4.

Mem(***small size2***) = membership of the size2 feature value in **small size2** membership function shown (black) in Figure 4.

Mem(***lower values of blobs4***) = membership of the blobs4 feature value in **lower values of blobs4** membership function shown (black) in Figure 4.

Mem(***not always sequential***) = 1 if the detector triggering is "not sequential," and 0 if the detector triggering is "sequential."

The justifications for the weights and membership functions for the systems described above have been previously provided in this section. In the air detonations, the same descriptions of target classes and weights are used regardless of the distance between the camera and a munition's detonation. In this case, size1 and size2 feature values are range dependent. To accommodate changes in range, either the membership functions for these features are modified, or the feature values themselves are range normalized.

Section 4 of this report provides examples of the feature vectors and confidence output values generated by the linguistic-fuzzy classifiers. This section also provides a discussion of how the confidence values are used to classify DSI events and provides a summary of results obtained on the DSI visible camera training set.

4. LINGUISTIC-FUZZY CLASSIFIER RESULTS

Table 3 provides the complete set of results obtained on the DPG visible camera training data set. The first column in the table provides the name of the file. The next seven columns provide the feature vector extracted from the data. The next six columns provide various confidence values generated using the linguistic-fuzzy classifiers described in Section 3. The next column provides the classification result. The final column provides comments regarding the classification result. No comment means the classification result is correct. This comment column points out false positives, false negatives, or improperly classified detonation modes. The table provides the results from 104 of 160 total "training" munition detonations' video segments. In many of the remaining "training" video segments, the munitions' detonations were not recorded in the video segment. In a few cases, a different means for overlaying the recording time and video counter position were used. This resulted in the differences in the contrast and color depth for these specific video segments (an artifact of the CODEC used to convert the video signals to AVI files).

The filenames associated with each munition's detonation event in the table also provide information about the event. The first three numbers after the T provide the test number. The DVV code tells us that this is DPG visible video data. The last two letters provide the specifics on the types and modes of detonations. An HE point detonation is indicated by HP, and a CB point detonation is indicated by CP. An HE air detonation is indicated by HA, and a CB air detonation is indicated by CA.

The six features that are in the next six columns are the feature vectors analyzed by the various fuzzy-linguistic classifiers. The absolute value of the delta gray feature is presented as Abs Dgray and is used as input for the classifier to separate the air from the point detonations. Orient is the orientation feature also used as input to the classifier to separate the air from the point detonations.

The delta gray (Dgray) feature is used in the classifier to separate HE from CB air detonations. The size1 feature (size1) is used in the classifier to separate HE from CB air and CB point detonations. The size2 feature (size2) is used to separate HE from CB point detonations. The B4 is the blobs4 feature, and SQ is the sequential feature. These features are also used to help separate HE from CB point detonations. The distribution of these features with a given explosive's detonation class was previously provided in this report and in References 2 and 3.

Table 3. Feature Vectors and Classifier Results for DPG Visible Camera Data Set

FILENAME	Abs DGray	Orient	DGray	Size1	Size2	B4	SQ	Air Conf	HE - Air	CB - Air	Point Conf	HE - Point	CB - Point	Class	Comment
T004DVV00CHP	25.45	-16.89	25.45	172	272	4	1	0.72	0	1	0.71	0.95	0	HP/CA (HP)	Indeterminate - False Pos
T006DVV00CHA	41.4	-40.06	-41.4	392	773	6	1	0.78	1	0	0	0	0	HA	
T011DVV00CHP	18.8	6.3	18.8	483	1368	1	1	0.6	0.6	0.8	0.71	0.81	0.32	HP	
T012DVV00CCP	4.39	-11.57	-4.39	56	117	1	1	0.03	0	0	1	0.66	0.95	CP	
T013DVV00CHP	16.53	7.31	16.53	289	424	1	1	0.4	0.31	0.85	0.71	0.87	0.32	HP	
T017DVV00CCA	43.32	-60.55	43.32	243	807	1	1	0.85	0.07	0.96	0	0	0	CA	
T019DVV00CCP	11.73	0	11.73	58	98	2	1	0	0	0	1	0.65	0.87	CP	
T023DVV00CHP	18.27	-18.61	18.27	145	279	3	1	0.58	0	1	0.71	0.95	0.04	HP	
T025DVV00CCA	29.76	-62.24	29.76	189	753	1	1	0.96	0	1	0	0	0	CA	
T028DVV00CHA	15.76	-65.33	-15.76	389	912	3	1	0.78	1	0	0.22	0	0	HA	
T029DVV00CCP	0.05	4.01	-0.05	37	124	3	1	0	0	0	1	0.66	0.83	CP	
T030DVV00CHA	42.14	-55.18	-42.14	461	1248	1	1	0.86	1	0	0	0	0	HA	
T032DVV00CHA	18.97	-61.48	-18.97	459	995	4	1	0.94	1	0	0	0	0	HA	
T033DVV00CHP	5.16	-12.59	5.16	165	210	3	1	0.05	0	0	1	0.98	0.48	HP	
T035DVV00CCA	21	-60.43	21	173	451	2	1	1	0	1	0	0	0	CA	
T036DVV00CHP	15.71	-45	15.71	261	845	4	1	0.78	0.16	0.91	0.23	0	0	CA (HP)	False Pos
T037DVV00CCA	36.5	-54.03	36.5	257	591	2	1	0.9	0.14	0.92	0	0	0	CA	
T038DVV00CCA	33.69	-55.37	33.69	233	468	1	1	0.92	0.02	0.99	0	0	0	CA	
T040DCC00CHP	15.87	-10.1	15.87	82	168	2	1	0.34	0	1	0.73	0.62	0.85	CP (HP)	False Pos
T044DVV00CCP	3.68	9.32	3.68	39	83	2	1	0	0	0	1	0.63	0.87	CP	
T046DVV00CHA	57.11	-58.18	57.11	544	968	1	1	0.77	0.6	0.8	0	0	0	CA (HP)	False Pos
T051DVV00CCA	36.82	-53.56	36.82	201	446	1	1	0.9	0	1	0	0	0	CA	
T053DVV00CCA	38.2	-69.24	38.2	162	375	2	1	0.89	0	1	0	0	0	CA	
T054DVV00CHA	12.11	-48.97	-12.11	569	944	3	1	0.71	1	0	0.71	0.81	0.04	HA	
T055DVV00CCA	34.62	-47.06	34.62	234	540	1	1	0.92	0.02	0.99	0	0	0	CA	
T058DVV00CCA	28.32	-54.67	28.32	121	373	1	1	0.97	0	1	0	0	0	CA	
T060DVV00CHA	12.49	-46.22	-12.49	403	821	1	1	0.71	1	0	0.71	0.81	0.32	HA	
T061DVV00CHA	22.37	-59.86	-22.37	343	657	1	1	1	0.99	0.01	0	0	0	HA	
T062DVV00CCA	39.44	-62.47	39.44	168	375	1	1	0.88	0	1	0	0	0	CA	
T064DVV00CHA	4.14	-71.57	-4.14	373	822	2	1	0.6	0.6	0	0.71	0.81	0.18	HP (HA)	Wrong Det Mode
T065DVV00CCA	37.27	-65.36	37.27	230	427	1	1	0.9	0	1	0	0	0	CA	
T066DVV00CHA	4.99	-39.29	-4.99	307	480	1	1	0.59	0.4	0.2	0.71	0.83	0.32	HP (HA)	Wrong Det Mode
T070DVV00CCA	35.96	-49.25	35.96	201	394	1	1	0.91	0	1	0	0	0	CA	
T071DVV00CHA	31.76	-50.87	-31.76	347	580	1	1	0.94	1	0	0	0	0	HA	
T072DVV00CHA	19.46	-54.91	-19.46	382	741	1	1	0.97	1	0	0	0	0	HA	
T073DVV00CHA	11.87	-66.68	-11.87	379	701	3	1	0.71	1	0	0.71	0.81	0.04	HA	
T074DVV00CCA	21.08	-57.61	21.08	185	426	1	1	1	0	1	0	0	0	CA	
T075DVV00CCA	43.75	-58.56	43.75	233	497	1	1	0.85	0.02	0.99	0	0	0	CA	
T077DVV00CHP	2.93	5.9	2.93	167	262	3	1	0	0	0	1	1	0.09	HP	

Table 3. Feature Vectors and Classifier Results for DPG Visible Camera Data Set (Continued)

FILENAME	Abs DGray	Orient	DGray	Size1	Size2	B4	SQ	Air Conf	HE - Air	CB - Air	Point Conf	HE - Point	CB - Point	Class	Comment
T079DVV00CCP	5.84	4.31	5.84	96	147	2	1	0	0	0	**1**	0.68	**0.87**	CP	
T080DVV00CHP	16.69	-18.43	16.69	350	612	5	1	0.45	0.6	0.8	**0.71**	**0.81**	0	HP	
T082DVV00CHP	25.52	-2.67	25.52	173	310	2	1	**0.7**	0	**1**	**0.71**	**0.95**	0.18	**HP/CA** (HP)	Indeterminate - False Pos
T084DVV00CCP	6.96	-45	6.96	58	107	2	1	**0.71**	0	**0.62**	**0.71**	0.57	**0.85**	CP	
T085DVV00CCP	9.63	0.23	9.63	60	121	2	1	0	0	0	**1**	0.66	**0.87**	CP	
T086DVV00CHP	4.31	-9.7	4.31	174	307	1	1	0	0	0	**1**	**1**	0.45	HP	
T087DVV00CHP	3.39	-71.57	3.39	216	311	6	1	0.6	0	0.6	**0.71**	**0.95**	0	HP	
T088DVV00CCP	9.39	29.86	9.39	82	140	1	1	0	0	0	**1**	0.68	**0.95**	CP	
T089DVV00CHP	5.3	-10.28	5.3	222	322	2	1	0.01	0	0	**1**	**1**	0.25	HP	
T090DVV00CHP	5.79	-7.38	5.79	270	408	2	1	0	0	0	1	**0.94**	0.25	HP	
T091DVV00CCP	6.29	5.2	6.29	63	106	2	1	0	0	0	1	0.65	**0.87**	CP	
T092DVV00CHP	6.41	-3.52	-6.41	164	277	3	1	0	0	0	**1**	**1**	0.05	HP	
T093DVV00CCP	4.4	-0.38	-4.4	38	82	1	1	0	0	0	**1**	0.63	**0.95**	CP	
T094DVV00CCP	3.35	0	3.35	45	75	2	1	0	0	0	**1**	0.63	**0.87**	CP	
T095DVV00CHP	0.37	-23.2	-0.37	193	325	4	1	0.27	0	0	**0.86**	**1**	0	HP	
T096DVV00CCP	11.4	-14.68	11.4	86	172	2	1	0.09	0	0	**1**	0.7	**0.87**	CP	
T097DVV00CHP	10.85	-10.69	10.85	253	356	5	1	0.01	0	0	**1**	**0.98**	0	HP	
T098DVV00CCP	7.2	-0.56	7.2	62	101	2	1	0	0	0	**1**	0.65	**0.87**	CP	
T099DVV00CCP	8.2	-48.48	-8.2	40	98	2	0	**0.71**	**0.51**	**0.6**	**0.71**	0.46	**0.91**	CP	
T100DVV00CHP	5.88	-9.55	5.88	182	341	4	1	0	0	0	**1**	**1**	0	HP	
T101DVV00CCP	11.39	12.44	11.39	74	111	3	1	0	0	0	**1**	0.65	**0.83**	CP	
T102DVV00CHP	6.48	-3.26	6.48	221	345	4	1	0	0	0	**1**	**0.99**	0	HP	
T103DVV00CHP	10.14	-10.15	10.14	265	393	2	1	0	0	0	**1**	**0.95**	0.25	HP	
T104DVV00CCP	7.59	10.07	-7.59	43	93	2	1	0	0	0	**1**	0.64	**0.87**	CP	
T105DVV00CCP	1.21	0	-1.21	57	80	3	1	0	0	0	**1**	0.63	**0.83**	CP	
T107DVV00CHP	18.28	-18.97	18.28	189	333	4	1	0.58	0	1	**0.71**	**0.95**	0	HP	
T108DVV00CHP	14.05	-19	14.05	213	314	2	1	0.26	0	0	**0.88**	**1**	0.25	HP	
T109DVV00CHP	17.96	-4.44	17.96	179	290	3	1	0.53	0	1	**0.71**	**0.95**	0.04	HP	
T110DVV00CCP	0.76	5.19	-0.76	68	111	2	1	0	0	0	**1**	0.65	**0.87**	CP	
T111DVV00CCP	3.5	2.34	3.5	53	80	1	1	0	0	0	**1**	0.63	**0.95**	CP	
T112DVV00CHP	7.67	-39.81	-7.67	257	380	2	1	0.6	0.45	0.46	**0.71**	**0.91**	0.18	HP	
T113DVV00CHP	3.79	-30.98	3.79	143	177	6	0	0.42	0	0.6	**0.71**	**0.84**	0.61	HP	
T118DVV00CHP	9.84	-29.17	9.84	203	295	4	1	0.39	0	0.71	**0.71**	**0.95**	0	HP	
T119DVV00CCP	7.07	-10.9	7.07	47	79	2	1	0.02	0	0	**1**	0.63	**0.87**	CP	
T120DVV00CCP	3.72	-11.44	-3.72	38	104	3	1	0.03	0	0	**1**	0.65	**0.83**	CP	
T121DVV00CHP	9.79	-45	-9.79	158	277	4	1	**0.71**	**0.77**	0.6	**0.71**	**0.95**	0	HP	
T122DVV00CCP	1.22	-5.11	-1.22	60	91	2	1	0	0	0	**1**	0.64	**0.87**	CP	
T123DVV00CHP	4.34	-20	-4.34	203	249	3	1	0.2	0	0	1	**1**	0.18	HP	
T124DVV00CCP	6.41	-21.8	6.41	20	72	2	1	0.24	0	0	**0.91**	0.63	**0.87**	CP	
T125DVV00CHP	4.42	-21.35	4.42	205	285	3	1	0.23	0	0	**0.94**	**1**	0.05	HP	

Table 3. Feature Vectors and Classifier Results for DPG Visible Camera Data Set (Continued)

FILENAME	Abs DGray	Orient	DGray	Size1	Size2	B4	SQ	Air Conf	HE - Air	CB - Air	Point Conf	HE - Point	CB - Point	Class	Comment
T126DVV00CHP	2.06	-18.54	2.06	221	265	5	1	0.17	0	0	**1**	**1**	0.05	HP	
T127DVV00CCP	1.4	-4.26	-1.4	17	46	1	1	0	0	0	**1**	0.61	**0.95**	CP	
T128DVV00CCP	4.95	0	4.95	20	48	1	1	0	0	0	**1**	0.61	**0.95**	CP	
T129DVV00CHP	8.09	-29.93	8.09	118	228	3	1	0.4	0	0.65	**0.71**	**0.69**	0.49	HP	
T130DVV00CCP	0.97	-18.43	0.97	60	158	4	1	0.17	0	0	**1**	0.69	**0.83**	CP	
T131DVV00CHP	4.38	-26.97	4.38	194	293	4	1	0.34	0	0.6	**0.74**	**0.95**	0	HP	
T133DVV00CHA	32.95	-46.78	32.95	514	1066	1	1	**0.93**	0.6	**0.8**	0	0	0	**CA** (HA)	False Pos
T135DVV00CCA	47.01	-52.81	47.01	251	516	1	1	**0.82**	0.11	**0.94**	0	0	0	CA	
T136DVV00CHA	3.4	-60.36	3.4	507	861	1	1	**0.71**	**0.6**	0	**0.71**	**0.81**	0.32	**HP** (HA)	Wrong Det Mode
T137DVV00CHA	40.71	-36.23	-40.71	401	736	1	1	**0.73**	**1**	0	0	0	0	HA	
T138DVV00CCA	43.07	-50.54	43.07	271	681	1	1	**0.85**	0.21	**0.89**	0	0	0	CA	
T139DVV00CHA	39.63	-60.68	-39.63	435	872	1	1	**0.88**	**1**	0	0	0	0	HA	
T140DVV00CCA	42.3	-57.82	42.3	224	632	1	1	**0.86**	0	**1**	0	0	0	CA	
T141DVV00CHA	29.01	-85.9	-29.01	899	1650	5	1	**0.66**	**1**	0	0	0	0	HA	
T143DVV00CCA	48.34	-60.64	48.34	239	471	1	1	**0.82**	0.05	**0.97**	0	0	0	CA	
T144DVV00CHA	44.63	-60.51	-44.63	446	784	2	1	**0.84**	**1**	0	0	0	0	HA	
T145DVV00CCA	46.8	-56.57	46.8	286	634	1	1	**0.83**	0.29	**0.86**	0	0	0	CA	
T146DVV00CHA	34.72	-53.8	-34.72	694	1280	8	1	**0.92**	**1**	0	0	0	0	HA	
T147DVV00CCA	42.26	-69.53	42.26	231	460	2	1	**0.86**	0.01	**1**	0	0	0	CA	
T148DVV00CHA	13.01	-62.68	-13.01	429	839	3	1	**0.71**	**1**	0	**0.71**	**0.81**	0.04	HA	
T149DVV00CCA	34.83	-59.87	34.83	221	481	2	1	**0.92**	0	**1**	0	0	0	CA	
T150DVV00CCA	43.26	-63.01	43.26	259	496	1	1	**0.85**	0.15	**0.92**	0	0	0	CA	
T153DVV00CHA	55.52	-52.88	-55.52	401	774	1	1	**0.77**	**1**	0	0	0	0	HA	
T158DVV00CHA	28.02	-53.84	-28.02	446	869	1	1	**0.97**	**1**	0	0	0	0	HA	
T159DVV00CCA	40.07	-59.46	40.07	251	497	1	1	**0.87**	0.11	**0.94**	0	0	0	CA	

The next six columns provide the confidence values generated by the various linguistic-fuzzy classifiers. The first step in using the classifier results is to determine whether the munitions detonation was either air or point. The confidence values provided in the **Air Conf** and **Point Conf** columns are used for this purpose. In general, a difference of 0.1 in this value is considered relevant. If the **Air Conf** is greater than the **Point Conf**, and the difference is > 0.1, the **Air Conf** value is highlighted in Red. In these cases, the event being analyzed is classified as an air detonation event. If the **Point Conf** is greater than the **Air Conf**, and the difference is > 0.1, the **Point Conf** value is highlighted in red. In these cases, the event being analyzed is classified as a point detonation event. In cases where the absolute value of the difference between the **Air Conf** and **Point Conf** is ≤ 0.1, than the results from these classifiers alone can not be used to separate point from air detonations. In these cases, the **Air Conf** and **Point Conf** values are highlighted in blue. This occurred 10 times in the 104 cases provided in the table. In these cases, as described later in this section, information from the other classifiers is used to classify the event.

In cases where the detonation event is definitively classified as either an air or point detonation (e.g., the value in one of these two columns in highlighted in red), we next look at the values of CB and HE confidences for this detonation class to generate the "final" classification result for the munition's detonation event. It should also be noted that the detonation mode can also be determined by other DSI sensors. For example, the outputs of four acoustic sensors can be used to determine the location (including height above ground) of detonation events. This information could be used in cases where the visible sensor did not provide definitive classification of the observed event as either an air or point detonation, or to reinforce the visible sensor classification. Again, we use a value of 0.1 as a meaningful difference in confidence values (and in this case, there was not a single incidence where an event was classified as either air or point detonation where the difference value was less than this threshold). When either the **Air Conf** or **Point Conf** value is highlighted in red, then we consider the confidence values associated with the corresponding HE and CB. The higher of these two values is highlighted in red, and the event is classified as this type of event. For example, on T159DVV00CCA (the last row of the table), the **Air Conf** has a value of 0.87, and the **Point Conf** as a value of 0. Consequently, the **Air Conf** value is highlighted in red. The HE Conf value (listed as **HE Air**) has a value of 0.11, and the CB Conf (**CB Air**) has a value of 0.94. Therefore, the CB Conf value is highlighted in red, and this event is classified correctly as a chemical air detonation event. As a second example, consider the case of T131DVV00CHP (on the last page of the table). In this case, the **Air Conf** has a value of 0.34, and the **Point Conf** has a value of 0.74. Because the **Point Conf** value is greater than the **Air Conf** value by at least 0.1, the **Point Conf** value is highlighted in red. The **HE Point** confidence has a value of 0.94, and the **CB Point** confidence has a value of 0. Consequently, the **HE Point** confidence value is highlighted in red, and the event is correctly classified as an HE point detonation.

There are 10 cases in the table where the absolute value of the difference between **Air Conf** and **Point Conf** values did not exceed 0.1. In these cases, we consider the highest of the confidence values for both of these detonation classes. Again, we consider 0.1 as a meaningful difference in confidence value. When the difference in the highest value of confidence for both detonation modes exceeds 0.1, the lower value is highlighted in blue, and the higher value is highlighted in red. In these cases, the red highlighted value is the "final" classification result. As an example, consider test T148DVV00CHA. In this case, the **Air Conf** and **Point Conf** values are both 0.71. Therefore, they are both highlighted in blue. The **HE Point** confidence value is 0.81, and the **CB Point** confidence value is 0.04. Also in this case, the **HE Air** confidence value is 1, and the **CB Air** confidence value is 0. Consequently, the **HE Point** confidence value is highlighted in blue, and the **HE Air** confidence value is highlighted in red. This munition's detonation event is correctly classified as an HE air event.

In cases where the difference in the highest confidence values for both detonation modes does not exceed 0.1, the detonation mode is considered indeterminate between the two highest confidence modes. As an example, consider the case of T004DVV00CHP. In this case, the **Air Conf** value is 0.72, and the **Point Conf** value is 0.71. Consequently, they are both highlighted in blue. The **HE Air** confidence value is 0, and the **CB Air** confidence value is 1. In this case, the **HE Point** confidence value is 0.95, and the **CB Point** confidence value is 0. Consequently, this event is considered indeterminate, and the **HE Point** and **CB Air** values are highlighted in blue. The event is classified as HP/CA. In this case, information from other

sensors could help in the classification. This effort, fusion between IR, visible acoustic, and seismic is on going. However, note that the confidence values highlighted in blue that were generated by the linguistic-fuzzy classifiers could be fused with either other sensor data features or sensor classification results to remove the indeterminate nature of this classification, and hopefully, bias classification towards the correct **HE Point** detonation event. Also note that if the **HE Air** confidence value is higher than the **CB Air** confidence value (but still close to the **HE Point** confidence level) in this case, then only the detonation mode would be indeterminate. There were only two indeterminate classification results in the 104 cases evaluated.

The classification results are also occasionally highlighted in Table 3. A lack of highlighting indicates that the classification result is correct. Indeterminate classification results that resulted in false positives are highlighted in light blue. False positives are highlighted in green. Finally, events where the detonation mode was incorrectly classified are highlighted in brown.

A review of the confidence values and classification results provided in Table 3 show the excellent job that the linguistic-fuzzy classifiers have done on this data set. Of the 104 events classified in the table, only 9 events were incorrectly classified. Three events were incorrectly classified in respect to detonation mode, but are correct in terms of detonation type and are consequently not considered as either false positives or false negatives. Six events were classified as CB when they were actually HE and as such are considered false positives. Of these six events, two were classified as CB because the classification result was indeterminate. No CB events were classified as HE events (i.e., there were no false negatives).

The results provided in the table are summarized as follows. The linguistic-fuzzy classifiers provided a 94% correct assessment of whether the detonation was from either an HE or CB round. The false positive rate is approximately 6%, and the false negative rate is 0. The linguistic-fuzzy classifiers also correctly classified the detonation mode (air versus point) in 97% of the cases where the linguistic-fuzzy classifiers correctly classified the round as either HE or CB. These results are consistent (actually slightly worse) than those that were obtained using the same linguistic-fuzzy classifiers on the DSI blind DPG visible camera data set.

The meaningfulness of the confidence values produced by each of the six linguistic-fuzzy classifiers is demonstrated by the classification results achieved on the DSI training and blind DPG visible camera data sets. In addition, there is significant variation in the confidence values that depends on how well the feature vector extracted from a given video record agrees with the target class linguistic descriptions and the specific fuzzy membership functions used in these systems. The variation in confidence value results in a method where there is valuable information for performing sensor and information fusion. As previously mentioned, the confidence values generated by the linguistic-fuzzy classifiers, as well as the feature values used as inputs to these classifiers, could be fuzed with other sensor classification results, and confidence and feature values to increase the confidence of classification, reduce false positive (or false negative) declarations, and to help deal more effectively with indeterminate classification results. The data in the table clearly demonstrate the benefits this classification method has provided in evaluating the feature vectors extracted from the DSI DPG visible camera data set.

5. CONCLUSIONS AND RECOMMENDATIONS

In this report, we describe a new method for developing event classifiers. With this method, target classes are described linguistically in terms of specific attributes that distinguish the class either from other classes or from clutter. Membership functions are then used to translate the values of the specific attributes (or features) to a value between 0 and 1. In this case, a value of 0 indicates that the feature value is outside the distribution indicative of an event class, while a value of 1 indicates that the feature value belongs to the event class. Next, weights are assigned to each of the attributes based on their importance in separating the various classes. Then, a weighted average is generated using this information as a means of estimating class confidence.

We apply this new method to the Disparate Sensor Integration (DSI) Program Dugway Proving Ground (DPG) visible camera training (and blind) data sets. The purpose of the test was to determine whether or not we could differentiate between CB and HE munitions based on the image they produce. In this case, we developed six linguistic-fuzzy classifiers. These systems work with a 7-element feature vector as input. We developed a two-step system. First, we separate airbursts from point detonations. Then, we differentiate between CB and HE munitions. In the case of the DSI DPG visible camera training data set, the linguistic-fuzzy classifiers provided a 94% correct assessment of whether the detonation was due to either an HE or a CB round. The false positive rate was approximately 6%, and the false negative rate was 0. The linguistic-fuzzy classifiers also correctly classified the detonation mode (air versus point) in 97% of the cases where the linguistic-fuzzy classifiers correctly classified the round as either HE or CB. These results demonstrate the viability of this approach to generate meaningful confidence levels. The same systems were also applied to the DSI DPG blind visible data set. However, because of the change in focal length that occurred between the training and blind data collections, two of the size features had to be range normalized prior to running the linguistic-fuzzy classifiers. Results slightly better than those described above were obtained on the DSI DPG blind visible camera data set.

Linguistic-fuzzy classifiers have also been developed to work with features and to classify munitions' detonations in the DSI Air Force infrared camera training and blind data sets. This work demonstrates the broad applicability of the linguistic-fuzzy classifier and will be described in detail in a future report.

Future work on the linguistic-fuzzy classifier is concentrating on the development and demonstration of methods to automatically generate fuzzy membership functions and the weights that are used in these systems. Once completed, this work will further broaden the applicability of this classifier design method.

The linguistic-fuzzy classifier provides a computationally simple, robust, and intuitive method for developing classifiers for many applications. With proper design of a system, desirable properties such as range invariance can be easily integrated into systems, making this approach broadly applicable to many classification problems.

We recommend that the linguistic-fuzzy classifier method be expanded to include data from other sensors (e.g., acoustic and seismic) that were part of the DSI test.

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LITERATURE CITED

1. Birenzvige, A.; Sickenberger, D.; Reyes, F. *Disparate Sensor Integration Program Description and Preliminary Data Analysis*; ECBC-TR-251; U.S. Army Edgewood Chemical Biological Center: Aberdeen Proving Ground, MD, 2002; UNCLASSIFIED Report (AD-B284 556).

2. Nelson, B.; Birenzvige, A.; Underwood, W. *Evaluation of an Optical Imager as a Detector for Chemical Munitions*; ECBC-TR-308; U.S. Army Edgewood Chemical Biological Center: Aberdeen Proving Ground, MD, 2003; UNCLASSIFIED Report (AD-B293 345).

3. Nelson, B.; Birenzvige, A.; Underwood, W.; Sickenberger, D. *CB Round Discrimination Fusing Visible and Infrared Camera Data.* Presented at the 2003 SPIE Conference, Orlando, FL, Volume 5099, pp 397-408, 2003.

4. Nelson, B.; Birenzvige, A. *Detecting Chemical and Biological Munitions Using Infrared Imaging Systems, Advanced Image Processing and Feature Extraction Methods, and Linguistic-Fuzzy Classifiers*; ECBC-TR-352; U.S. Army Edgewood Chemical Biological Center: Aberdeen Proving Ground, MD, 2004; UNCLASSIFIED Report.